TITLE: Cameva, A Methodology for Estimation of Target Detectability

CAMEVA, A METHODOLOGY FOR ESTIMATION OF TARGET DETECTABILITY

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1. SUMMARY

This paper will present a methodology for computerised evaluation of camouflage effectiveness. The methodology is implemented in software at Danish Defence Research Establishment (DDRE) under the acronym CAMEVA. Basic input is a single image comprising a highly resolved static target as well as a proper amount of representative background. Separate target and background images can also be handled. Target and background regions are manually selected using the computer's standard pointing device (i.e. the mouse). From the input data, CAMEVA predicts the target detectability as a function of the target distance. The detectability estimate is based on statistical distributions of features extracted from the imagery, establishing a multidimensional feature space. In the feature space, the Bhattacharyaa distance measure is applied as an estimator of the separability between the target and the background. The intention is that the extracted features should resemble those applied during the human perception process. Typically, contrast and various measures of edge strength are applied. The Bhattacharyaa distance establishes a relative separability, while the absolute detection range is obtained by deriving a relation between the Bhattacharyaa distance and the estimated target resolution, at range. Thus by introducing parameters of the sensor, typically the human unaided eye, detectability as a function of the range is obtained. The methodology will not reflect individual observer performance but is aimed at providing an estimate of the optimal detection performance, given the selected set of features. During the choice of features and of sensor parameters, other perception mechanisms, than the human observer performance, can be modelled with this methodology. The paper will discuss theoretical and practical aspects of CAMEVA. Validation and application examples, including results on the NATO RTO/SCI-012 SEARCH_1 and SEARCH_2 datasets, will be presented together with other data.

Keywords: evaluating camouflage effectiveness, target detectability, detection range estimation, Bhattacharyaa distance, SEARCH_1 and SEARCH_2 data analysis

2. INTRODUCTION

CAMEVA is a methodology developed at the Danish Defence Research Establishment (DDRE) for computerised CAMouflage EVAluation and for estimation of target detectability. Input is a single digitised image comprising a highly resolved target as well as a proper amount of background. Based on that, CAMEVA predicts the target detectability as a function of range, in principle from relatively close range to infinite.

The methodology is based on measuring the dissimilarity between the statistical distributions of features on the target and on the background.

The need for objective and cheap methods for the evaluation of the effectiveness of camouflage measures was the original motivation for the development of CAMEVA. The methodology has however been applied in other tasks as well, including characterisation of sensors, evaluation of image processing algorithms and multiple sensor fusion algorithms.

2.1. History

In the late seventies and early eighties it was recognised at DDRE, that digital image processing was becoming available as a useful tool for solving many tasks of relevance to the military. Clearly it was important also to consider image-processing methods in relation to the evaluation of camouflage effectiveness.

The advantages were obvious. If such methods were available, the camouflage effectiveness could be assessed without the presence of costly equipment and significant numbers of human observers, as it is needed in field trials and in photo-simulation experiments. Evidently there were attractive economical aspects of this, but also the technical and scientific aspects were considered, such as the desire for speedy, reproducible results, that are easily documented.

For various reasons camouflage activities at DDRE were reduced to a minimum during a period of the late eighties and early nineties. The existing software was "mothballed" and further development within the regime of DDRE was cancelled during that period.

New tasks related to camouflage evaluation and to the estimation of detectability have however led to a resumed activity within this field. The old work was brushed up and that, together with new research in the field, led to the development and implementation of CAMEVA.

3. SYSTEM OVERVIEW

The aim with CAMEVA is to model the potentially achievable performance of a detection task. The aim is not to provide detailed models of the functionality of the very complex physiological and intellectual processes related to a human detection task. The aim is rather to establish limits to the performance that can be achieved, based alone on the information hidden in the scenario. Thus CAMEVA establishes an upper limit for the probability of detection.

A detection task is most often carried out by observers using the unaided eye, but this particular methodology is also applicable to observers using electro-optical equipment and as

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a reference metric for optimality during the design of detection algorithms.

The high-level diagram of Figure 1 shows the main building blocks of CAMEVA.

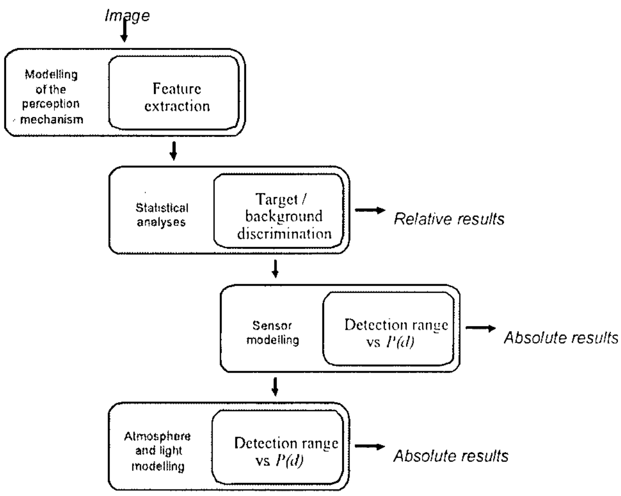

Figure 1: The main building blocks of CAMEVA.

The input is an image presumed to be of good quality. I.e. the image should have a high resolution compared with the degradations caused by the sensory system being modelled, and atmospheric transmission effects should be negligible. This assumption is needed due to the simulation strategy applied in CAMEVA. The results should be limited by the system parameters, and not by the quality of the input data.

The first processing block is the feature extraction. The target strength is based on the measurement of the strength of certain features on the target relative to the strength of these features on the background.

The choice of which image regions belong to the target and which regions belong to the background is based on an interactive selection procedure carried out by the system operator.

The choice of features depends on the characteristics of the presumed perception mechanism. If the unaided human eye is applied, features corresponding to those applied during the human perception process should be used. Or if some other perception mechanism is assumed, the features corresponding to that mechanism should be applied. A typical choice of features in the case of the unaided human eye is contrast, texture, shape, and edge-content sensitive features.

This is not a perception model in the more rigorous definition of this term, rather than it is a type of preprocessing attempting to extract the same attributes from the data, as those used during the processing performed by the actual perception mechanism. In the current context we will however denote this processing "the perception model" since this is the step in the processing where the characteristics of the psycho-visual processes are being modelled.

Based on the features, the analysis kernel estimates the statistical distribution of the features of the target and of the background. A measure of the difference between the distributions is established. This provides a relative measure of detectability, i.e. a measure that is independent of the target range. Finally the relative difference measure is weighted according to the degradation introduced by the limited resolution of the sensor and thereby also introduces the target distance as a system parameter.

Atmospheric influences on the results are currently not implemented. Consequently the underlying assumption is ideal atmospheric conditions. This is recognised as an important issue for the continuing improvement of the system. The idea is to propose an atmospheric weight factor to the measure of separability; similar to the way the sensor characteristics are modelled into the system. It has been demonstrated[2] that this, under certain conditions, can be done with a simplified transmission loss model.

The perception model typically used, is a simplified model of human vision, based on contrast and edge detection. The method applied in the analysis-kernel is based a statistical approach for measuring the separability between distributions, known as the Bhattacharyaa[3] distance.

The following sections will discuss various aspects of this methodology. The statistical decision theory involved is discussed initially, since this is also applied to illustrate the motivation for the choice of features. This discussion is followed up later, with considerations of atmospheric transmission and light conditions. Validation examples are shown at the end of the paper.

4. STATISTICAL DECISION

The statistical decision procedure is based on a feature vector $\mathbf{x} = \{x_1, x_2, \ldots, x_n\}$. Each x represents one feature. We claim that detection is possible when the multidimensional distribution function of features on the target is sufficiently different from the corresponding background distribution.

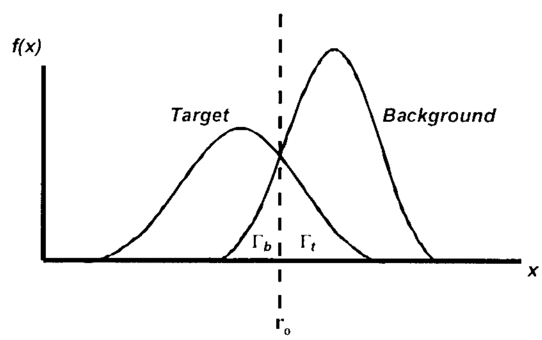

Figure 2: Distribution densities of target and background, with decision errors represented by Γ_t, Γ_b and the decision threshold r_o.

We further claim that estimates of the target and background distributions, based on high-resolution imagery, can be utilised to predict the corresponding distributions as a function of the distance. That is the same as postulating that basically the distributions are inherent properties of the target and the background. For the moment we shall neglect any external influence (i.e. atmosphere etc.) that violates this assumption.

4.1. Basic decision theory

The target and background distributions are exemplified for a single feature in Figure 2. In the detection case, assuming a one-sample observation, the fraction of the distribution overlap denoted Γ_t represents the error of missing a target with r_o as the detection threshold. Hence the probability of missing the target is $P(b)\Gamma_t$, with $P(b)$ as the a priori probability of a random sample being background. The errors represented by Γ_b (i.e. the false alarm rate) are irrelevant in this situation where we are evaluating a known target relative to the background. Correspondingly the probability of detection $P(d)$ is:

$$P(d) = 1 - P(b)\Gamma_t \qquad (1)$$

In general, with an n-dimensional distribution Γ_t is determined over the n dimensions of the observation vector.

By introducing the sampling and assuming k independent samples of the target, the detection probability becomes:

$$P(d) = 1 - P(b)\Gamma_t^k \qquad (2)$$

4.2. The Bhattacharyaa Distance

Given that parametric distributions are unknown, together with the general problems of analytically determining the distribution overlap $\Gamma = \Gamma_t + \Gamma_b$, we introduce the Bhattacharyaa[3] distance D, that is a measure of how different two distributions are:

$$D = -\ln\left\{ \int_{-\infty}^{\infty} \sqrt{f_t(\mathrm{x}) f_b(\mathrm{x})}\, dx \right\} \qquad (3)$$

The integral is an approximation to Γ.

In the detection case where the target qua the distance occupies only a small fraction of the total field of view (FOV), a reasonable approximation to $P(b)$ is $P(b) \approx 1$. Furthermore it follows from $P(b) \approx 1$ that Γ_b is negligible compared to Γ_t and thus Γ_t is an approximation to the total distribution overlap.

Using $P(b) \approx 1$ and $\Gamma_t \approx \Gamma$, a minor rewrite of equation (2) provides:

$$P(d) \approx 1 - \exp\{k \ln\{\Gamma\}\} \qquad (4)$$

The distribution overlap is represented by the integral within the Bhattacharyaa distance, thus $D \approx -\ln\{\Gamma\}$. In the limiting case of identical distributions it is easily seen that $D=0$, and of totally different distributions that $D \to \infty$.

With the Bhattacharyaa distance we have:

$$P(d) \approx 1 - \exp\{-kD\} \qquad (5)$$

We see that in the case of identical distributions $P(d)=0$, which is reasonable due to $P(b)=1$. This means that there is virtually no chance of hitting the target by random choice. Similarly by totally different distributions $P(d)=1$, which is also reasonable since this allows detection of an almost infinitely small target.

4.3. Limited Resolution

We introduced k as the available number of independent samples of the distribution. In the visual detection task k will depend on the target size A, the target distance L and how well the eye is capable of independently sampling the FOV. The last parameter we shall denote "the effective minimum resolvable field of view" θ_k. The target size is normally trivial and the target distance is a variable parameter of the simulation (i.e. we are aiming at detection curves as a function of the distance). Thus with the assumption that θ_k is also known, the target resolution k is determined by the geometry of the scenario and we obtain the probability of detection as a function of the range:

$$P(d, L) = 1 - \exp\left\{ -\frac{DA}{L^2 \theta_k^2} \right\} \qquad (6)$$

Where k is:

$$k(L) = \frac{A}{L^2 \theta_k^2} \qquad (7)$$

In the case of different horisontal and vertical resolution characteristics θ_k^2 is replaced by the product of the separated horisontal and vertical components $\theta_{k,h}$ and $\theta_{k,v}$.

4.4. Multidimensional Feature Spaces

Numerically computation of the Bhattacharyaa distance in the multidimensional feature space is quite complex and in fact not necessary. From the definition of the Bhattacharyaa distance we obtain with the assumption of independent features that:

$$D = \sum_{l=1}^{n} D_n \qquad (8)$$

We may therefore conveniently write D as the sum of the individual Bhattacharyaa distances for each feature.

This result is important since it implies that the complexity involved with the computation of estimates of multidimensional distributions can be avoided.

Whether this assumption is valid depends on the choice of features.

4.5. Feature extraction

Selection of features is a nontrivial task. This is illustrated in Figure 3. On the upper left "triangles" image, the two "targets" are easily detected visually. A statistically based metric, operating solely on the contrast, provides zero difference between both two targets and the background.

Clearly other features are also involved with the detection process in the example, although the contrast is still relevant. The three additional features in the Figure illustrates this:

It is evident that each of the features reflects different properties of the input data. We will consider the target and background regions of the added features:

The strength of the horizontal edges are applicable for detection of the upper right target (which we will denote "target A"), as these edges are relatively strong in the background, and virtually non-existent in the target. The lower left target (denoted "target B") is more difficult to detect, and the only useful cue is missing edge at the top of the target.

With respect to the vertical edges, target A is once again easily detected. This time due to the strong vertical edges.

Target B is difficult, although still detectable, due to the discontinuities of the edges. But basically the edge-strengths of both the target and the background are the same.

With respect to the isotrope edge features both targets are - roughly speaking - equally difficult to detect.

We see that the choice of features is vital to the result. In the case of an analysis (i.e. an algorithm) applying only contrast processing, this single feature might be sufficient. But in other situations more complex features should be applied.

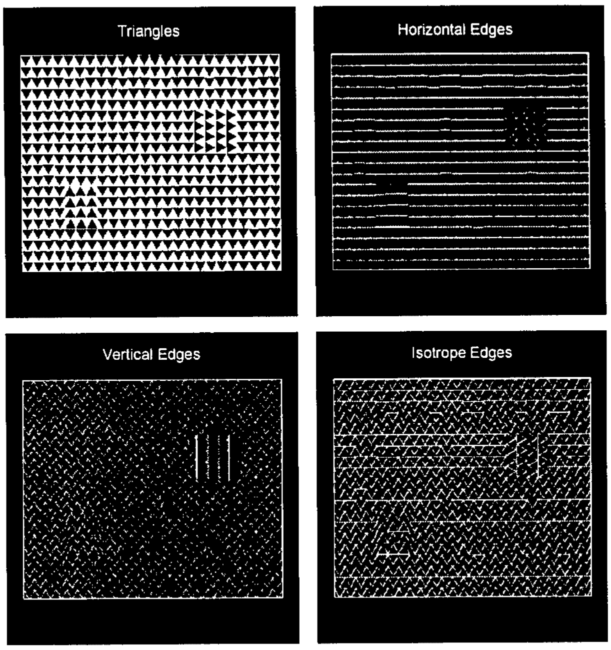

Figure 3: Four different features of a simple image with two target. Both the targets and the background are triangles. The unprocessed (the contrast feature) and three additional features based on edge strength.

By application of the relative analysis-part of CAMEVA, (i.e. computing the Bhattacharyaa distance), to the triangle input image with all four features, the computational results should reflect the qualitative assessment above. The results are shown in table 1.

The Bhattacharyaa distances correspond nicely to the results obtained from the visual assessment: D_C is about the same for both targets, which means that based on contrast both targets are equally easily detected. D_H and D_V each are relatively strong in target A, while D_H is weak in B. The isotrope component of the target is about the same for both targets, which is also reasonable since the have equal components of diagonal edges.

Typical features that have been applied in the application of CAMEVA to visual detection tasks are the four features used in this example.

4.6. Atmospheric and light conditions

While $k(L)$ provides a method of limiting the resolution due to distance, it does not model the effect of atmospheric transmission loss and light conditions (i.e. day or night). The current work will in principle assume infinite visibility and full daylight. A simple model for the atmospheric influence on the Bhattacharyaa distance have been considered[2], providing a Bhattacharyaa distance as a function of L. Likewise a simple model for the influence of the light is considered. Non of these modelling concepts have however been validated.

4.7. Training of algorithm

Training of CAMEVA is in principle a very simple procedure. There is only one parameter (θ_k) that is not easily determined, neither by the physical setup of the experiment, nor by the optics of the sensor.

The parameter θ_k depends on psychological factors such as motivation and on experience with visual target acquisition.

Table 1: Target/background Bhattacharyaa distances for the four different features of the triangle image.

Target	Feature			
	Contrast [D_C]	Horizontal edge [D_H]	Vertical edge [D_V]	Isotrope edge [D_I]
A	0.0336	0.1129	0.0894	0.0666
B	0.0363	0.0140	0.0501	0.0556

Based on the physiology of the eye[1], figures in the order of 0.2 mr are obtained. In the detection task however, where the observer is unable to focus on the target, this figure is typically too optimistic. Experimental data[1] prepared at DDRE have shown that θ_k=2.0 mr is a useful value for a group of non-military observers. In the case of highly trained observers, other values of θ_k may have to be used.

4.8. Practical aspects

To illustrate that the methodology applied in CAMEVA is quite widely applicable, we will discuss a few aspects related to the practical use of CAMEVA. This illustrates however also that this technique requires a skilled operator, with a general understanding of the problems related to the effectivity of camouflage measures.

- Data collected with detectability as the main purpose are typically long-range images. Often data taken at close range and with the target in the actual background have not been collected. In those cases experiments[6] with the application of CAMEVA have been made with separated target and background images. Clearly there are problems related to that procedure, but attempts have been made to align the internal target image-dynamics as well as the target-background image-dynamics in this type of data, thus allowing the target and background statistics to be taken from different images. Preferably however this procedure should be avoided, and should also be avoidable in experiments designed specifically as input to CAMEVA.
- CAMEVA is a human-in-the-loop process. With the input imagery, the operator must decide which image regions to apply as target and which to apply as the background. An example of this procedure is illustrated in Figure 4. Clearly that procedure is sensitive to the selection of in particular the background region, which is not well defined, and the operator must be careful, in order to produce meaningful results. Related to that is

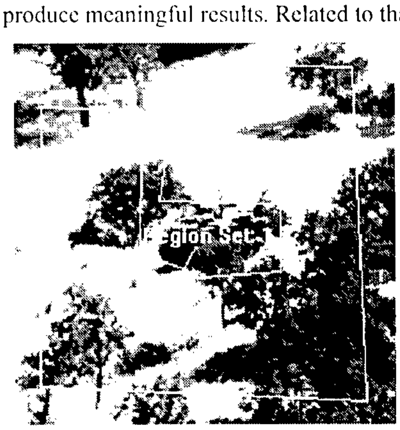

Figure 4: A subsection of an image of the SEARCH_1[5] dataset, with overlay of target and background regions applied by CAMEVA.

also the fact that the results are basically a kind of averaging across the target region and the background region. I.e. if the target contains isolated bright spots, acting as cues to the observer, the averaging is problematic.

- In a classical camouflage-scenario the most efficient camouflage blends the target into the local background. CAMEVA is basically designed with that scenario in mind. In other scenarios, for example desert with scattered trees and bushes, the most efficient camouflage will sometimes be one that most closely matches the target to the scattering structure. Thus analysis made against the local background in that case are meaningless. In those situations the background region used as input to CAMEVA must be selected from the relevant part of the images, and not from the local background, like for example regions with trees and bushes.

Other scenarios can be thought of where there are problems related to this kind of methodology. In most cases however a skilled operator will be capable of producing useful results.

5. RESULTS

Results based on three different datasets are presented. Initially we discuss the JPRIS dataset that was specifically collected as a means for testing and calibrating CAMEVA. Secondly we discuss the application of CAMEVA to the SEARCH_1 and SEARCH_2 datasets.

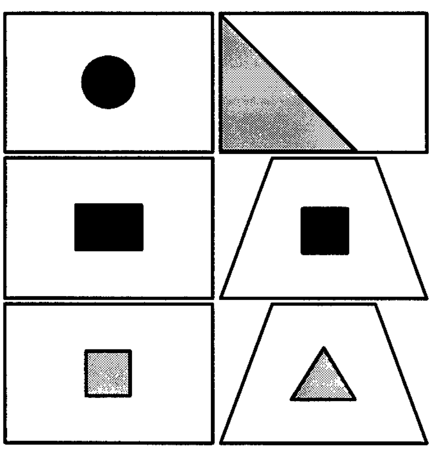

Figure 6: The types of panels applied as targets, not shown to scale. The panel areas vary from 0.20 m^2 to 0.90 m^2, while the signature elements vary from 0.025 m^2 to 0.26 m^2.

5.1. The JPRIS dataset

The jpris dataset is based on an observer field test[1] conducted by DDRE.

The experiment was designed as an observation trial with observations performed by the unaided eye.

Targets consisted of 12 artificial panels of 6 different types, either rectangular or trapezoidal as illustrated in Figure 6. Each panel was covered by a piece of green texture mat and a signature was attached to the surface, to allow identification when observed.

The background was a line of vegetation consisting of trees and bushes. All of the panels were presented against that same background.

The total length of the observation path was approximately 600 m with seven observation posts from long range (665 m) to close range (100 m) arranged along the path.

A total of 40 observers recorded the point of detection and the point of identification, starting at long range and approaching the target panels along the observation path. The observers were "semi-trained" in the sense that they were scientific and administrative civilian personnel working for the Danish military and some had, due to their scientific duties, some experience with observation tasks.

To support the computational analysis slides were taken from the observation posts. Each target panel was analysed with CAMEVA and detection curves obtained. Similarly detection curves were extracted from the field trial results. Comparison of the results, as averages across the observer population, is illustrated in Figure 7.

It is seen that the theoretical results to a very high degree describes the results of the field-trial. From these results it seems indeed, that the human acquisition process, under certain conditions, can be described as a statistically process derived from first principles.

The parameter θ_k=2.0 mr is however determined from the same population as were used as observers during the experiment.

One important error source is not taken into account during this experiment, namely the presence of eye-catching cues in the background close to the target. It is believed that the unexpected result for target-panel two is due to an abnormal intensity distribution (very dark) in the immediate neighbourhood of the target. There is evidence within the data that indicates that the observers have detected the background, and not the target itself.

5.2. The SEARCH datasets

The SEARCH_1 and SEARCH_2 datasets comprise a total of 44 images of six military vehicles recorded at different target distances and with the targets presented against different backgrounds.

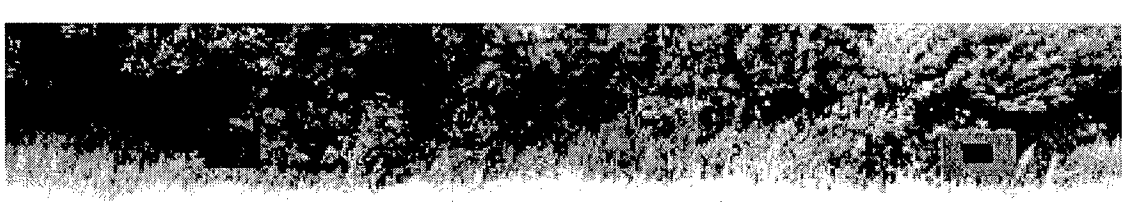

Figure 5: Example on the deployment of target panels in the JPRIS experiment.

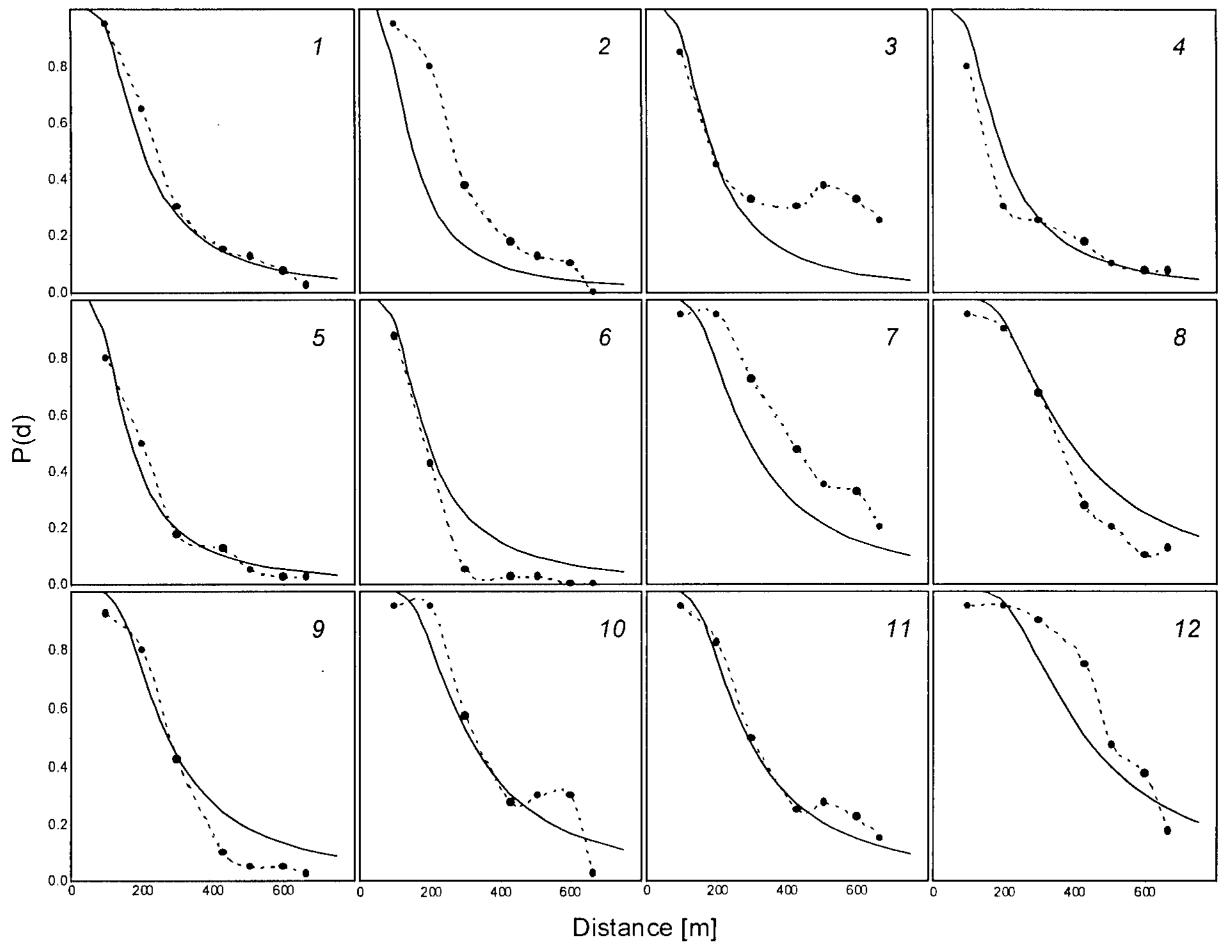

Figure 7: Detection curves obtained as a result of the DDRE JPRIS experiment compared with results of CAMEVA. Theoretical results are the solid curves, while the experimental results are the dotted curves

The only difference between SEARCH_1 and SEARCH_2 is the resolution of the digitised imagery, that is 1536 × 1024 pixels in the case of SEARCH_1 and 6144 × 4096 in the case of SEARCH_2.

Data are available in digitised form as full colour images as well as grey-level images. Each scenario is available as a pure background image, as well as an image with the target in the background. Furthermore close-up images of each target are provided at three different aspects. Ground truth is provided as binary target masks with each image. Target distances vary from about 800 m to 6 km.

The SEARCH data are collected and distributed by TNO-HFRI[1], and have kindly been provided for the application of the data to computational techniques estimating human observer performance in detection tasks.

TNO-HFRI has also conducted photo-simulation observer tests on the data, providing a baseline for the testing of computational methods for prediction of detectability and search time. A second photo-simulation experiment[7] on a subset of the SEARCH_1 data was prepared by DCTA[2]

[1] TNO Human Factors Research Institute, Soesterberg, The Netherlands

[2] Defence Clothing and Textiles Agency, Colchester, The United Kingdom

CAMEVA was applied to the 44 images of the dataset and probability of detection was computed as a function of the target range. $P(d)$ at the actual target range was computed and compared with the photo-simulation results. CAMEVA was not trained on the SEARCH datasets prior to its application to them.

Cross comparisons of the results from CAMEVA, the TNO experiment and the DCTA experiment are sumarised in the bar-graphs of Figure 8.

As described CAMEVA normally provides detection curved as a function of the distance. In this case and to aid comparison of results $P(d)$ is computed at the actual target distance only.

6. CONCLUSIONS AND FURTHER WORK

Through the development and the study of CAMEVA, we have established a correlation between results obtained by human observers in the detection task and the results provided by CAMEVA. It is also evident however that several aspects of CAMEVA need further research to provide a more robust system. The most important areas are summarised below:

CAMEVA depends strongly on the skills of the operator during the selection of target and background regions. Rather than consider an automated procedure for that, which we believe is practically impossible, it is considered to produce a kind of catalogue that will set up typical scenarios together with proposed operator methodologies to cope with these.

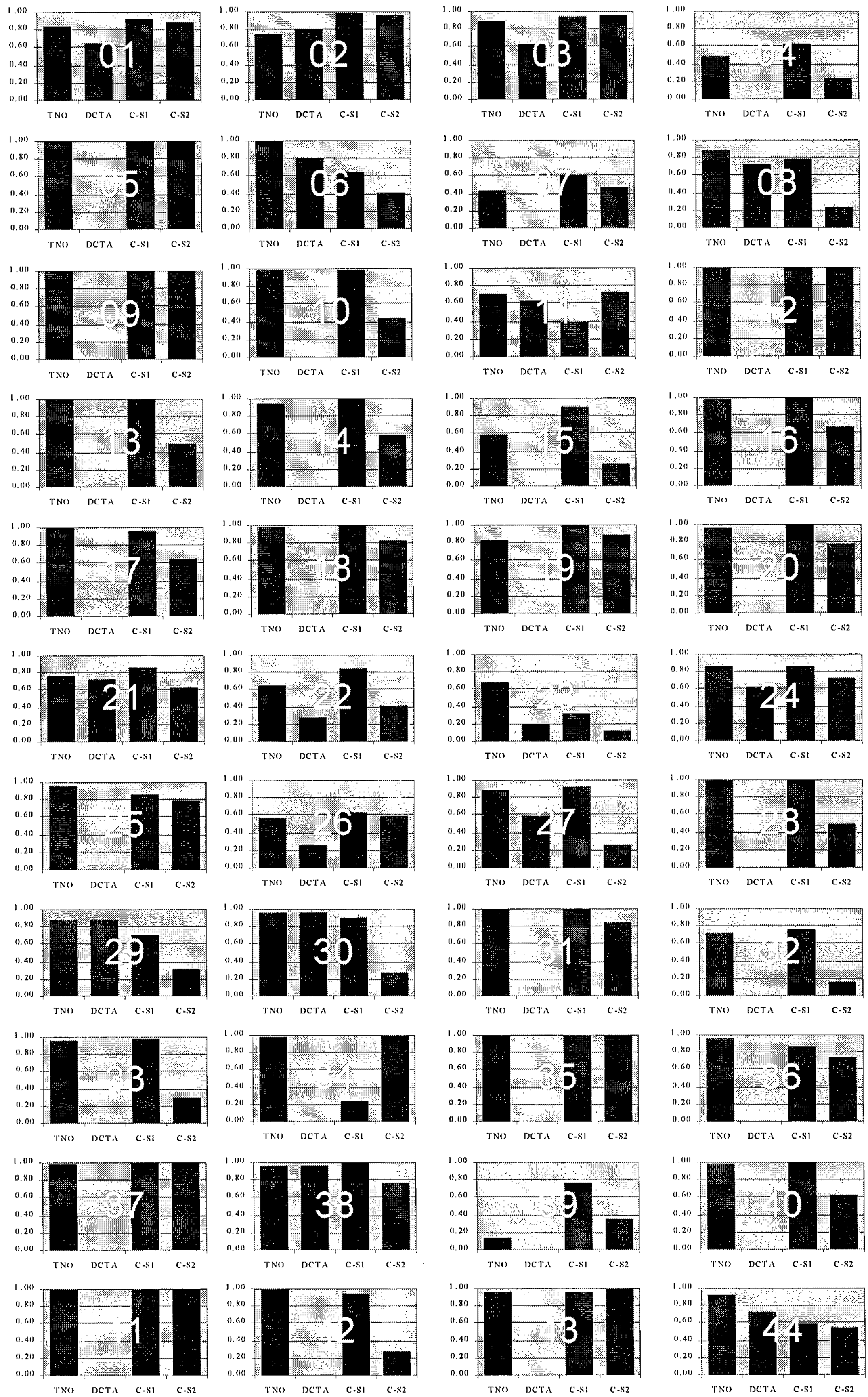

Figure 8: ***P*(*d*) estimated by CAMEVA applied to SEARCH_1 (C-S1) and SEARCH_2 (C-S2), compared with observer experiment results.**

It is considered important to implement a proper procedure for modeling of atmospheric transmission loss and of light conditions. Fundamentals for these sub-models have been investigated, but still need validation.

The current choice of features is not necessarily optimal. Certain aspects of detection are currently not modeled. A typical example is the cueing provided by long straight lines. Further features need to be investigated and in some cases algorithms for their implementation must be developed.

7. REFERENCES

1. Dannenberg, E. and G. Hvedstrup Jensen, *A Theoretic and Experimental Study of Human Visual Target Acquisition Based on Digital Image Analysis*, Danish Defence Research Establishment, DDRE 1982/19, 1982.
2. Hvedstrup Jensen, *Some Aspects of Statistical Separability and Detection Probability*, Danish Defence Research Establishment, DDRE 1981/30, 1981.
3. Fukunaga, Keinosuke, *Introduction to Statistical Pattern Recognition*, Academic Press, New York 1972.
4. Birkemark, C. M., *Computerised Evaluation of Camouflage Measures (CAMEVA)*, Danish Defence Research Establishment, DDRE F-175, 1994.
5. Toet, A; Bijl, P; Kooi, F. L. and Valeton, J. M.: *Image data set for testing search and detection models*, TNO Human Factors Research Institute, Soesterberg, The Netherlands, TM-97-A036, 1997.
6. Birkemark, C. M., *Application of CAMEVA to the SEARCH_1 dataset*. Danish Defence Research Establishment, DDRE N-4, 1998.
7. Houlbrook, A., *Observer Tests on Digitised Imagery*, DCTA S&TD Research Memorandum 98/01, 1998.
8. Birkemark, C. M., *Theoretical and Practical Aspects of CAMEVA*, Danish Defence Research Establishment, DDRE N26, 1997.